



## **Progress in LIBS for Land Mine Detection**

**by Jennifer L. Gottfried, Russell S. Harmon, and Aaron LaPointe**

**ARL-TR-5127**

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## **Progress in LIBS for Land Mine Detection**

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14. ABSTRACT The ability to interrogate objects buried in soil and ascertain their chemical composition in-situ would be an important capability enhancement for both military and humanitarian demining. Laser-induced breakdown spectroscopy (LIBS) is a simple spark spectrochemical technique using a pulsed laser. Recent developments in broadband and man-portable LIBS provide the capability for the real-time detection of all elements at very high sensitivity in any target material. This technological advance offers a unique potential for the development of a rugged and reliable man-portable or robot-deployable chemical sensor that would be capable of both in-situ point probing and chemical sensing for land mine detection. In this study, broadband LIBS spectra were acquired under laboratory conditions for more than a dozen different types of antipersonnel and antitank land mine casings from four countries. A set of antitank land mine simulants was also acquired. Subsequently, a statistical classification technique (partial least-squares discriminant analysis) was used to discriminate land mine casings from the simulants and to assign “unknown” spectra to a mine type based upon a library classification approach. Overall, a correct classification success of 99.0% was achieved, with a misclassification rate of only 1.8%.					
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## 1. Introduction

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Land mines are a direct threat on the battlefield and remain a significant problem for civilians in areas of current and former conflict. Some 15,000–20,000 people in more than 90 countries fall victim to land mines each year (1, 2). These explosive hazards cannot be efficiently removed using current humanitarian demining approaches (3). At present, land mine detection is generally conducted in a manner similar to that employed half a century ago. A handheld metal detector is used to identify a subsurface anomaly that may be a buried land mine. In humanitarian demining, meter-wide lanes are searched for anomalies by swinging a metal detector back and forth just above the ground surface. When the metal detector receives a signal, the suspected area is probed to determine whether or not it contains a buried land mine. This is also the procedure used for military postoperational land mine clearance, although the new AN/PSS14 handheld mine detection system that combines a metal detector with a ground-penetrating radar was deployed for the first time in 2003 on a limited basis by U.S. forces in Afghanistan. To investigate the anomaly detected by a land mine sensor system, a human deminer uses a thin, tapered prodding device to determine if the anomaly is a solid object and, if so, whether or not it is a land mine. This is a very tedious and sometimes uncertain approach. Thus, there is a particular need for a deminer's soil prodder that will differentiate between buried antipersonnel mines and other subsurface objects (4).

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## 2. LIBS for Land Mine Discrimination

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Laser-induced breakdown spectroscopy (LIBS) is a simple spark spectrochemical technique that uses a pulsed laser to create the spark. The technique has many attributes that make it an attractive tool for chemical analysis, particularly its potential as a field-portable sensor for geochemical analysis (5, 6). LIBS is relatively simple and straightforward, so skilled analysts are not required. Little to no sample preparation is required, which eliminates the possibility of sample adulteration through improper handling or storage, or cross-contamination during sample preparation. LIBS provides a real-time response and a simultaneous detection and analysis of all elements. The laser plasma is formed over a very limited spatial area so that only a small sample (pg-ng) is engaged in each laser microplasma event. All instrument components can be made small and rugged for field use, and LIBS sensors can be operated either as a point sensor or in a standoff detection mode.

Broadband LIBS, which captures the spectral region from 200 to 940 nm (in which all elements emit light), is a sensor technology capable of discriminating among different types of plastic land mine casings through a statistical approach that compares the LIBS spectrum acquired for an unknown sample against a spectral library (7–11). The discrimination of different explosive and energetic materials using LIBS has also been demonstrated (12–18). Thus, LIBS has the potential to be a single-sensor technology that can detect and discriminate both the casing of a land mine and its explosive contents. The recent development of man-portable/backpack LIBS sensor systems (7, 9–11, 16, 19, 20) that utilize small, rugged lasers (which are very suited for field use) has opened up the possibility for LIBS to be used as a confirmatory sensor technology for land mine detection.

More than a dozen different types of antipersonnel and antitank mines and a broad range of natural and anthropogenic materials (“clutter”) of the kind likely found within the soil of a conflict area or former conflict area were analyzed previously in our lab using a LIBS system (9, 11). A spectral library was created, and a simple linear correlation was used to classify the LIBS spectra. The results of that study are summarized in table 1. Although LIBS was able to distinguish the mines and clutter objects very well (94.6% correct mine identification), it was not able to identify specific mine types (80.4% correct identification). The goal of this study was to apply recent advances in the chemometric analysis of LIBS data (16) to the problem of land mine detection to determine if specific mine types could be identified with greater accuracy.



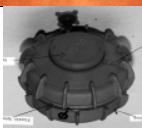





Table 1. Initial land mine casing results (9).

<b>Target (No. of Samples)</b>	<b>Correct Mine/No-Mine ID (%)</b>	<b>Correct Sample ID (%)</b>
Land mine casings (56)	94.6	80.4
Plastics (24)	83.3	79.2
Wood and cardboard (5)	100	100
Rocks (5)	100	100
Metal (10)	100	80.0
<b>Total (100)</b>	<b>93.0</b>	<b>82.0</b>

For this study, 3000 single-shot spectra of 41 inert mine casings (see table 2 for description of mines) and 7 mine simulants (1 wood, 2 black plastic, and 4 nylon) were acquired with a custom laboratory LIBS setup designed to accommodate large antitank mines (see figure 1). This U.S. Army Research Laboratory (ARL) system consisted of a Big Sky CFR400 laser (1064 nm, 90–150 mJ, 10-ns pulse) and an Ocean Optics LIBS2500+ broadband spectrometer that recorded LIBS plasma light emission over the spectral range from 200 to 940 nm. The light from the laser-induced plasma was collected and focused with a parabolic mirror onto the seven-fiber optic bundle delivering the light to the spectrometer. For each land mine casing and simulant, 1 cleaning shot was taken followed by 25 successive shots in two different locations (for a total of 50 single-shot spectra per sample). Single-shot spectra of the land mines are shown in figures 2 and 3, and spectra of the mine simulants are shown in figure 4. The strongest emission lines observed in the spectra have been identified and labeled. Atomic emission from the atmosphere contributes to the oxygen and nitrogen lines in all the spectra.



Table 2. Description of land mines.

Mine Type	Country of Origin	Quantity	AP/AT	Photo <sup>a</sup>
PMA-1A	Yugoslavia	14	AP	
M14	USA	9	AP	
PMN-1 <sup>b</sup>	Russia	6	AP	
TS-50	Italy	2	AP	
VS-MK2 <sup>b</sup>	Italy	2	AP	
TNG-M80	USA	1	AT	
VS-HCT2	Italy	1	AT	
TMA-3	Yugoslavia	1	AT	
TM-62P3	Russia	1	AT	
POM	Unknown	1	AT	Not available

Note: Antipersonnel (AP) and antitank (AT) land mines were provided by Aaron LaPointe (U.S. Army Night Vision and Electronic Sensors Directorate).

<sup>a</sup>Photos obtained from ORDATA online (21).

<sup>b</sup>Spectra of both the rubber top and the plastic bottom of the mine casing were acquired.



Figure 1. Photo of custom LIBS setup for land mine identification.

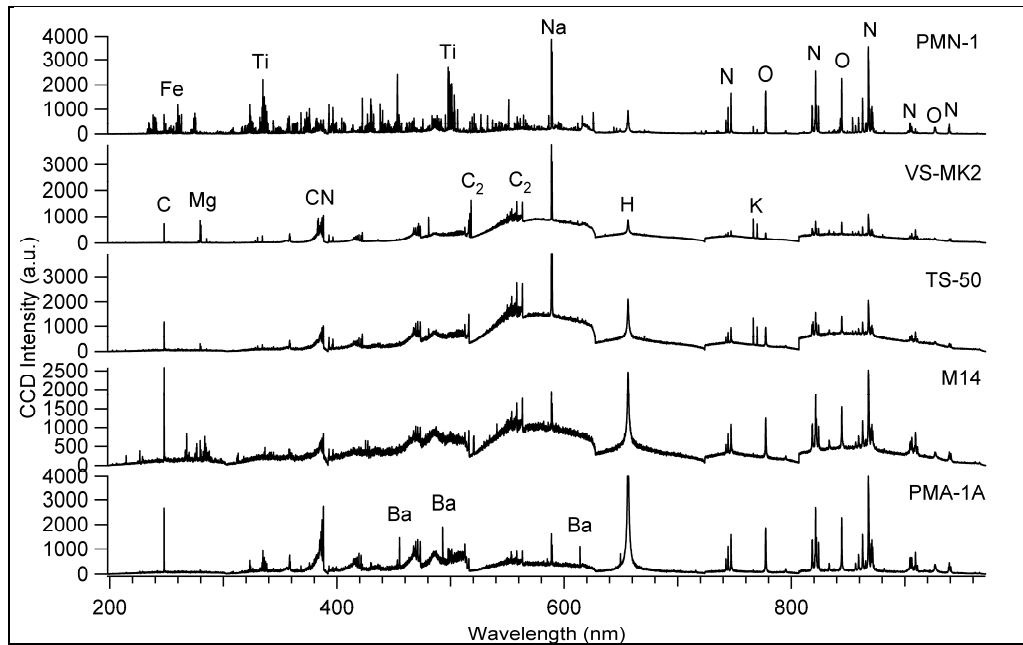


Figure 2. Single-shot LIBS spectra of antipersonnel land mine casings.

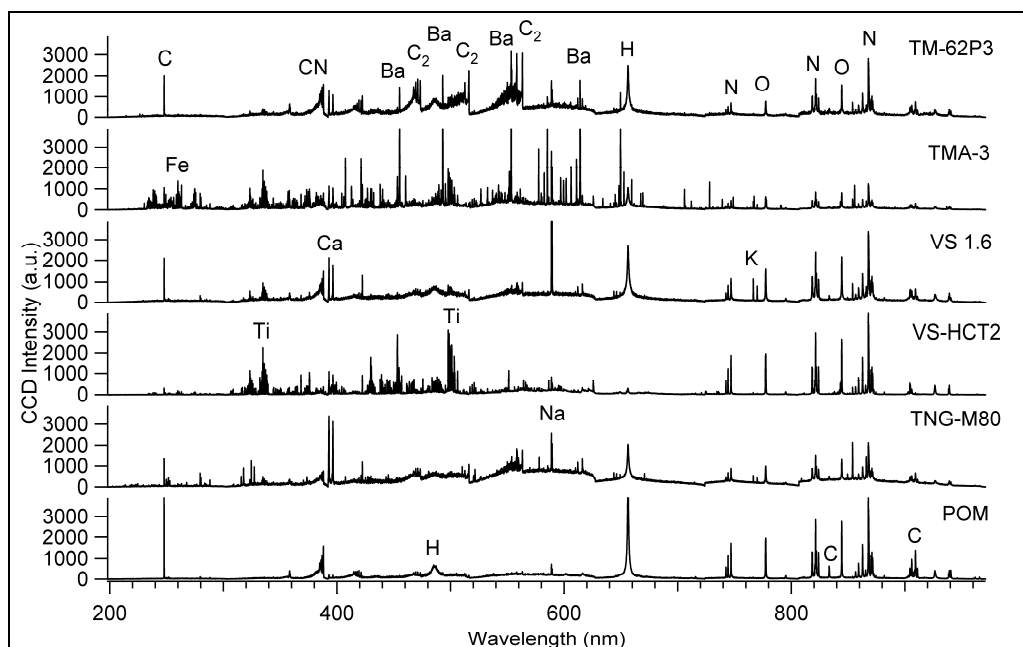


Figure 3. Single-shot LIBS spectra of antitank land mine casings.

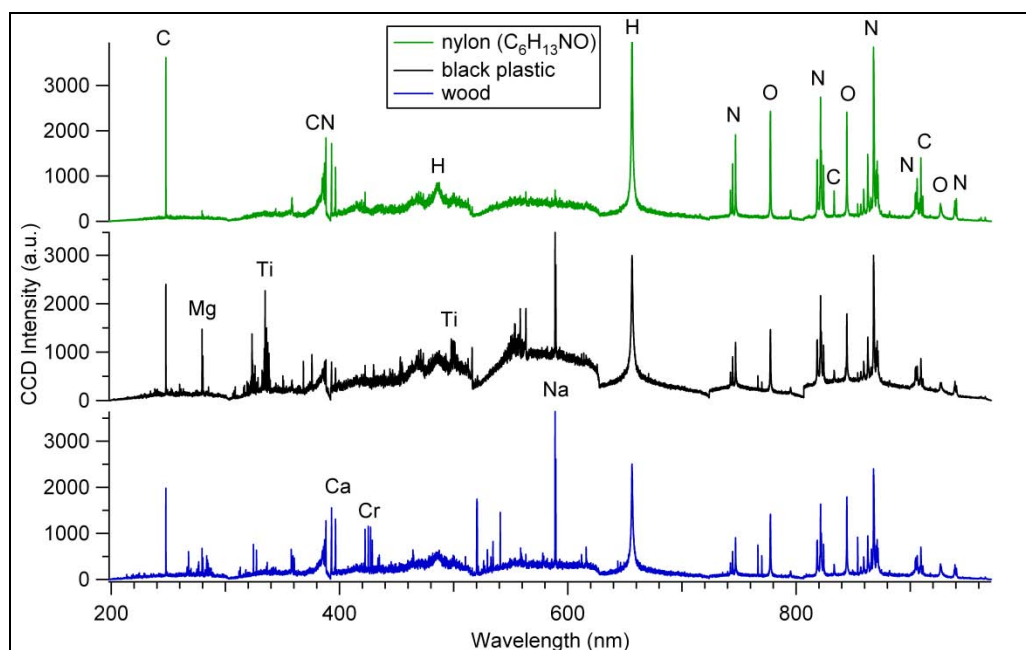


Figure 4. Single-shot LIBS spectra of land mine simulants.

As shown in this study (figures 2 and 3) and previous work (7–11), broadband LIBS analysis has demonstrated observable differences in land mine casings composition. To extend the LIBS approach to the problem of land mines at an operational level, the identification issue must be addressed. The big advantage of broadband LIBS, i.e., capturing the entire portion of the LIBS spectrum from 200 to 940 nm, is based on the idea that every material yields a unique LIBS spectrum. This being the case, a LIBS spectrum should provide a “fingerprint” of the material analyzed, and LIBS spectra of different materials should be distinguishable one from another by chemometric analysis.

Principal components analysis (PCA) is a chemometric technique that finds linear combinations of variables, i.e., principal components (PCs), which describe major trends in the data. PCA enables data compression and information extraction, and has previously been applied to LIBS spectra of biological and chemical warfare agent simulants (22, 23) and explosive residue samples (13–16) at ARL. Although PCA is not a classification technique, it provides a useful tool for identifying whether samples are the same or different and what variables are responsible for the differences. Twenty single-shot broadband spectra for each of 36 land mines (including spectra from the top and bottom of mines with separate cases and caps) and 5 mine simulants were used to build a PCA model. Spectral preprocessing involved normalization followed by mean-centering. The PCA scores are linear combinations of the original variables and contain information on how the samples relate to each other. The loadings contain information on how the variables (i.e., spectral wavelengths) relate to each other; mathematically they are the eigenvectors of the covariance matrix describing the variables. By considering the scores and loadings simultaneously, the variables responsible for the differences between samples can be identified.

The loadings for PC1 (describing 60.58% of the variance in the data set) show that the most important peaks in the model correspond primarily to the C, CN, C<sub>2</sub>, O, N, and Ca content of the land mines (figure 5). Because most of the land mines contain similar amounts of C, H, N, O, and Ca, the PCA model is unable to distinguish between the types of land mines and simulants (figure 6). When different types of land mines are considered individually, however, some interesting patterns emerge. For example, spectra of six PMN-1 mines were acquired. A plot of scores for the PMN-1 mines (figure 7) shows that mine nos. 16 and 17 are grouped together, separate from the other four PMN-1 mines (sample nos. 18–21). A comparison of the LIBS spectra (figure 8) reveals that mine no. 16 (and 17) has a stronger LIBS signal than mine no. 18 (and 19–21). In addition, spectra of both the rubber top of the mine and the bottom plastic case show distinct differences that are captured by the PCA model (figure 7). The rubber-like top parts of the PMN-1 mines have more Ca, CaO, and CaOH emission lines than the bottom (plastic-like) parts. Comparison of the scores plot (figure 7) with the loadings plot for PC1 vs. PC2 (figure 9) reveals that the separation between the top and bottom portions of the mine in the PCA scores plot is due to the higher Ca content in the top material, and the separation between mine nos. 16 and 17 and 18–21 likely reflects differences in the plasma temperature (since the separation is caused by the relative intensities of Ca atomic and ionic emission lines).

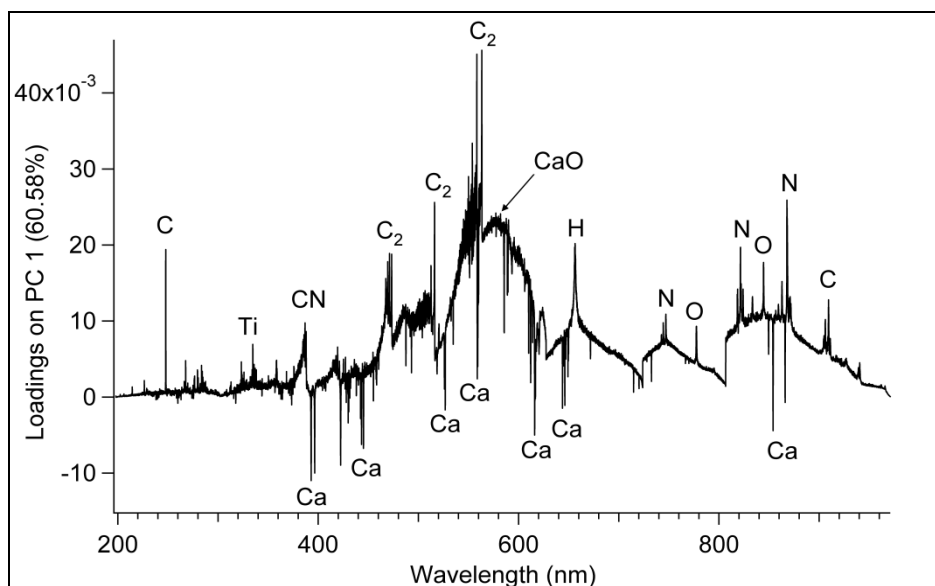


Figure 5. Loadings plot for PC1 for the PCA model built using 1000 LIBS spectra from 36 different land mines and 5 mine simulants.

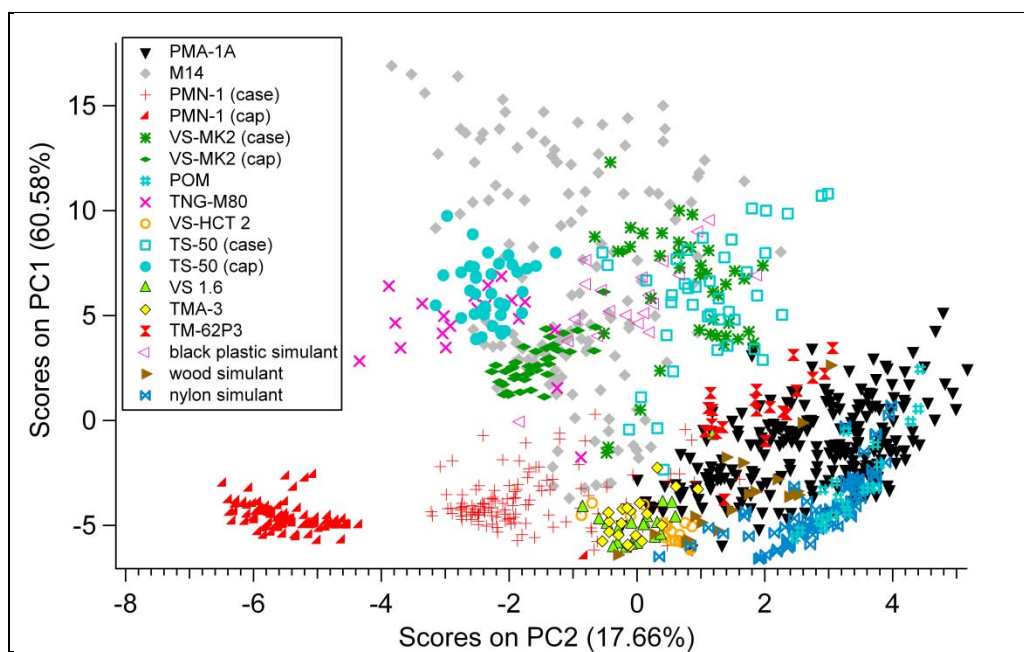


Figure 6. Scores plot of PC1 vs. PC2 for the PCA model built using 1000 LIBS spectra from 36 different land mines and 5 mine simulants.

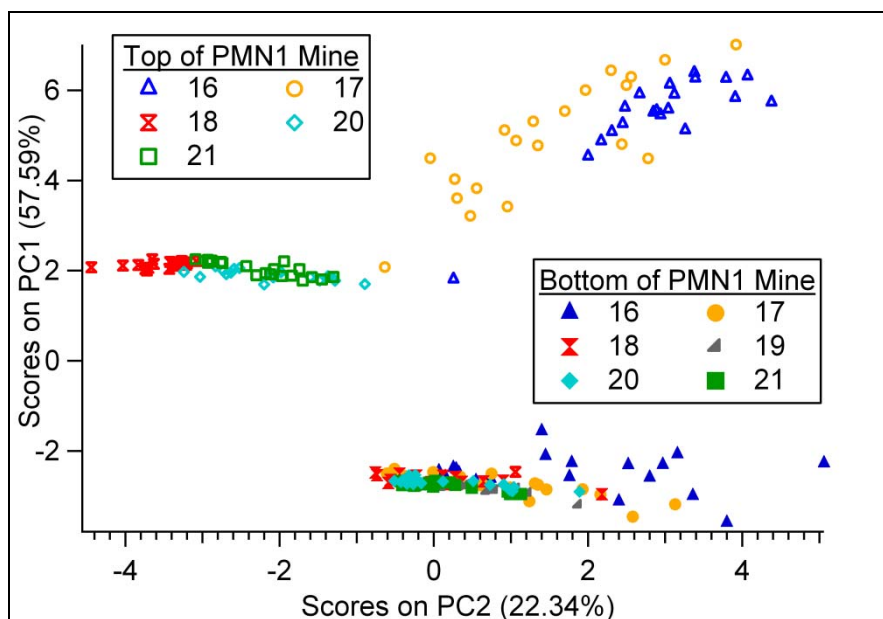


Figure 7. Scores plot of PC1 vs. PC2 for the PCA model built using 220 LIBS spectra from 6 different PMN-1 land mines (top and bottom). The cap for mine no. 19 was not available.

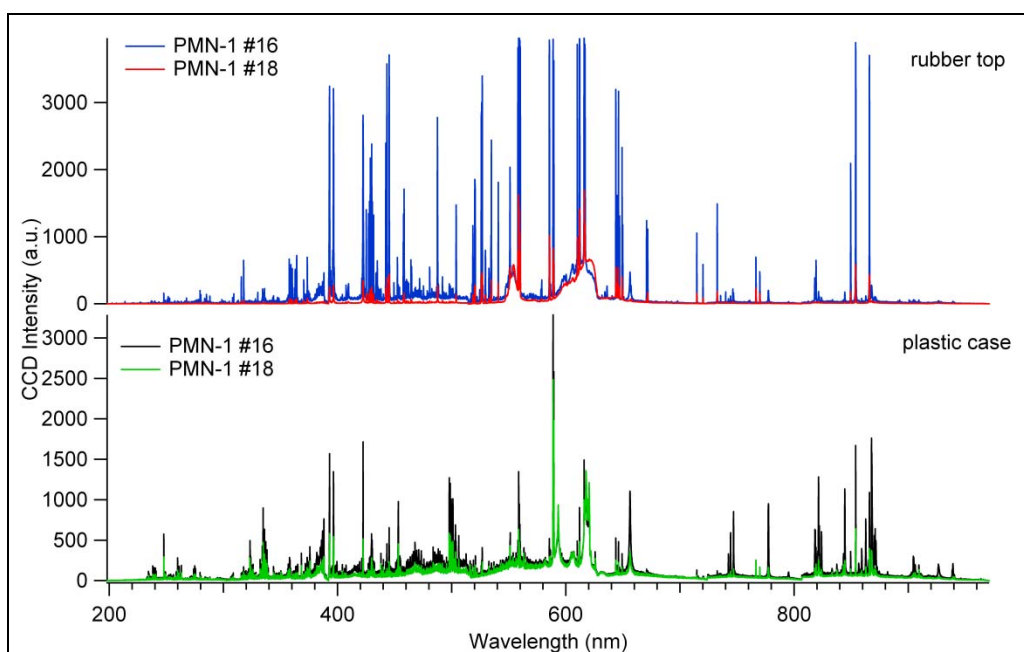


Figure 8. LIBS spectra of the top cap and bottom casing of two PMN-1 land mines.

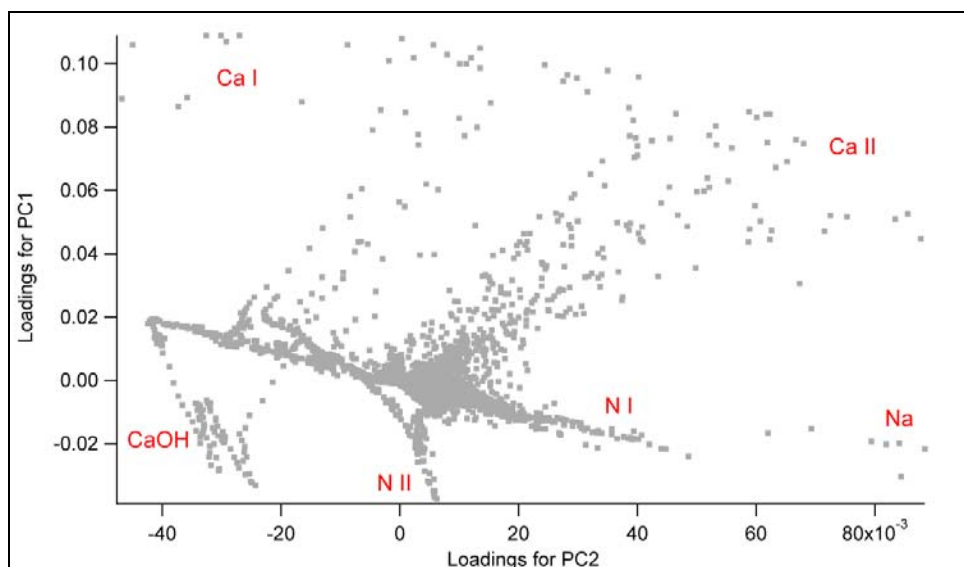


Figure 9. Loadings plot for PC1 vs. PC2 (PCA model based on the 6 PMN-1 mines). Comparison with the scores plot in figure 7 shows which spectral features contribute to the separation between the PMN-1 mines.

Partial least-squares discriminant analysis (PLS-DA) is a supervised, multivariate least-squares analysis technique that has shown to be extremely useful for hazardous materials classification with LIBS (14–17). In PLS-DA, the predictor variables (called “latent variables” [LVs]) are generated while simultaneously considering both intraclass and interclass variance. This is in contrast to PCA, which only considers the total variance of the entire data set. By maximizing the differences between sample classes (i.e., mine types), more subtle differences in the LIBS spectra are described by the PLS-DA model. A PLS-DA model was built using 17 sample classes consisting of 20 single-shot spectra each of 12 PMA-1A mines, 7 M14 mines, 6 PMN-1 cases, 5 PMN-1 caps, 2 VS-MK2 cases, 2 VS-MK2 caps, 2 TS-50 cases, 2 TS-50 caps, 1 POM-AT mine, 1 TNG-M80, 1 VS-HCT 2, 1 VS 1.6, 1 TMA-3, 1 TM-62P3, 1 wood mine simulant, 1 black plastic mine simulant, and 4 white nylon mine simulants. Twenty latent variables were chosen to describe the model spectra based on cross-validation (contiguous block method).

Because the model uses 20 LVs for optimal class discrimination, interpreting the loadings for each LV (in order to determine which wavelengths in the model are most useful for class separation) is complicated. The variable importance in projection (VIP) scores for each class are essentially a weighting of the regression vector and show which variables are important for separation between the classes in the model (24, 25). A variable with a VIP score close to or >1 can be considered important in a given model. As figure 10 shows, the VIP scores (which combine the LVs that contribute to each class) reflect the contributions of minor impurities to the LIBS spectra of the mines. Instead of trying to separate the different mines on the basis of common emission lines C, CN, C<sub>2</sub>, and Ca (see figure 5), the PLS-DA model is able to discriminate the mines based on differences in their trace metal content (Cu, Ba, Ti, Cs, Mg, etc.).

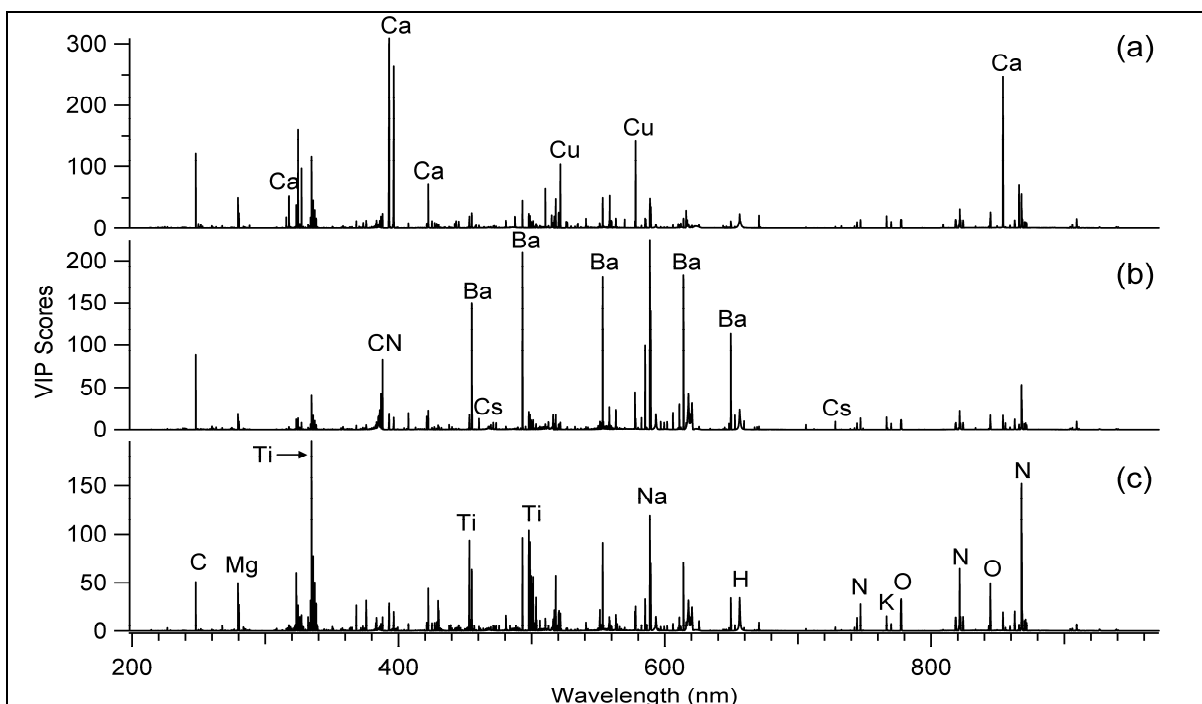


Figure 10. VIP scores for 3 of the classes in the 17-class PLS-DA model: (a) TNG-M80, (b) TMA-3, and (c) VS-HCT 2.

For each target class in the model, the likelihood that a given sample spectrum belongs to that class is predicted based on a value of 0 to 1. A value closer to 0 indicates that the sample is not in the modeled class, while a value of one indicates that the sample is in the modeled class. A threshold between 0 and 1 (above which a sample is considered in the class) is automatically calculated by the software using Bayesian statistics in order to minimize the number of false positives and false negatives (24). A validation set consisting of 30 additional spectra from each mine/simulant in the model was tested against the model. Based on the calculated thresholds for each sample class, 1485 out of 1500 test spectra fell above the threshold in the appropriate class, resulting in 99.0% correct classification for the validation set (table 3). The misclassification rate for the validation set was 1.8%. Of the misidentifications, 2.6% resulted in a mine simulant being identified as a mine (false positives), and 1.6% resulted in a mine being identified as a simulant (false negatives). The majority of the misidentifications (95.8%) were between mine types.



Table 3. PLS-DA results for validation test set consisting of 1500 additional LIBS spectra of the mines and simulants included in the model.

Test Spectra (No.)	Model Classes (No. Above Bayesian Threshold)																
	352	1	0	0	0	2	3	3	15	2	0	15	10	14	0	6	11
PMA-1A (360)	0	209	0	0	0	0	2	54	0	0	0	13	0	0	3	12	0
M14 (210)	2	0	180	0	1	0	1	0	4	5	3	2	0	1	0	1	0
PMN-1 case (180)	0	0	0	150	0	0	0	0	0	0	0	1	0	0	0	0	0
PMN-1 cap (150)	0	0	0	0	59	0	8	1	0	0	0	3	0	0	0	15	0
VS-MK2 case (60)	0	0	1	0	0	60	0	0	0	0	0	0	0	0	0	0	0
VS-MK2 cap (60)	0	0	0	0	21	0	59	3	0	0	0	0	0	0	1	1	0
TS-50 case (60)	0	60	0	0	0	0	0	60	0	0	0	4	0	0	0	1	0
TS-50 cap (60)	1	0	0	0	0	2	0	0	28	1	0	0	0	0	0	0	11
POM AT (30)	5	0	0	0	0	0	0	0	1	30	0	0	0	0	0	0	0
TNG-M80 (30)	0	0	4	0	3	0	0	0	2	0	30	0	0	0	0	0	0
VS-HCT 2 (30)	0	0	0	1	0	0	0	1	0	0	0	30	0	0	0	0	0
VS 1.6 (30)	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	1	0
TMA-3 (30)	22	0	0	0	0	0	0	0	0	0	0	4	3	30	0	0	2
TM-62P3 (30)	0	5	0	0	0	0	0	0	0	0	0	14	0	0	29	0	0
Wood simulant (30)	3	3	0	0	13	0	0	0	0	0	0	0	0	0	0	29	0
Black plastic simulant (30)	0	0	0	0	0	0	0	0	16	1	0	7	0	0	0	0	120
White nylon simulant (120)																	

A second test set of 50 spectra each for 6 mines and 2 simulants not included in the model, as well as spectra of the POM-AT mine acquired at a lower laser energy (90 mJ compared to the 150 mJ used for the model spectra), were tested against the PLS-DA model. When the Bayesian threshold was used to determine classification, the test set resulted in 98.6% correct classification and 4.6% misclassification. Of the misclassified spectra, 8.6% represented false positives and 0.1% represented false negatives. When the Bayesian threshold was used as a criterion for class membership, each single-shot spectrum could classify with more than one sample class (since the sample may lie above the threshold for more than one class). The percentage of correct classifications therefore refers to the diagonal elements of the confusion matrix (test sample class vs. model class), while the percentage misclassification refers to the off-diagonal elements (see table 3). For the second test set, an alternate method for determining class membership was applied. If the predicted probability for a test sample is >50% for a particular class, the sample is considered part of that class; however, if a test sample does not have a predicted probability >50% for any class in the model (or for more than one class), it is considered unclassified. When only the Bayesian threshold is used, the decision to classify a test sample with a particular model class is much less restrictive (resulting in more true positives as well as more false positives). The second method for class determination allows for the possibility that the sample does not match any of the classes in the model and prevents a sample from being grouped with more than one class. The results from the classification of the second test set are shown in table 4. The percentage of correct classification is now only 45.2% with 54.4% of the spectra unclassifiable; however, only 0.4% of the spectra are misclassified. Despite the difficulty in classifying two

M14 mines and the PMN-1 mine with their respective classes in the model, they were correctly identified as mines by the model 100% of the time. Overall, 99.3% of the mines in the test set were correctly identified as mines (regardless of type), but 35 of the black mine simulant spectra and all 50 of the wood mine simulant spectra were incorrectly identified as mines. Although the PLS-DA model includes 14 mine types, only three simulant types are included; increasing the number and type of clutter objects in the model will improve the predictive ability of the model to determine mine/no mine classification for sample types not included in the model.

Table 4. PLS-DA results for second test set of mines and simulants not included in the model.

Sample	No. Correct	No. Misidentified	No. Unclassified	Mine/No Mine ID
Three PMA-1A mines	141/150	0/150	9/140	149/150
Two M14 mines	8/100	1/100	91/100	100/100
One PMN-1 mine <sup>a</sup>	24/100	0/100	76/100	100/100
POM mine (low energy)	38/50	0/50	12/50	48/50
Black mine simulant	15/50	0/50	35/50	15/50
Wood mine simulant	0/50	1/50	49/50	0/50

<sup>a</sup>Spectra of both the casing and cap were acquired.

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### 3. LIBS as a Confirmatory Sensor for Demining

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An ideal land mine detector would detect and identify both the exterior casing and the contained explosive charge. LIBS has demonstrated such a dual capability, with unique broadband spectra successfully acquired under laboratory conditions for explosive materials and both metal and plastic antipersonnel and antitank land mines. With the recent progress made toward realizing man-portable LIBS, the concept of a LIBS demining probe for a confirmation land mine detection sensor now seems within reach. The idea is a backpack-size system that would contain a minilaser in the handle of a deminer's probe, with light delivered to and collected from the tapered tip of the probe and analysis made by touching the buried object. Such a capability could also be deployed by a robot for unmanned land mine detection (19).

The LIBS-based deminer's probe would be similar in form and material composition to the current generation of prodders in use within the humanitarian demining community, i.e., having a thin, ~30- to 40-cm-long end-tapered probe that joins a barrel-style handle. The probe would also allow for the delivery of an inert gas (e.g., He or Ar) to the tip of the probe, with the tapered tip of the probe designed to protect the ends of the optical fiber from both damage and soil obstruction during insertion. The probe handle would contain a pulsed laser capable of delivering >30-mJ pulse power. The laser signal would be directed through a set of optics (also

contained in the probe handle) to an optical fiber contained in the hollow probe that would transmit both the laser signal and the returned plasma light to the LIBS-spectrometer system that would be contained either in a backpack worn by the user or in a “pelican-type” case carried by the user. An analysis could be made rapidly and reliably by touching the buried object. Then, a laser spark would be created and a plasma generated on the surface of the object after preliminary “cleaning” shots to remove surface soil particles and expose a fresh material surface. The resultant plasma light would be captured by the fiber optic in the probe tip and transmitted through the fiber optic in the prod and handle to the broadband spectrometer. The broadband LIBS spectrum obtained would be background corrected by software in the onboard computer in real time and then compared with a spectral library of land mine casings, explosives, and common environmental clutter objects to determine if there was a positive correlation. A spectral match with a reference spectrum in either the land mine casings or explosives library would be declared a positive response that required marking and excavation. This specially designed LIBS system for land mine detection could be used as a confirmatory sensor for both humanitarian and military demining, but it also has the potential to be used in a variety of noncountermine applications (e.g., homeland security, forensic, environmental cleanup, geoscience, and bioscience applications) that would benefit from chemical analysis of an undisturbed substance in the field in real time.

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